Climate Research for Development (CR4D)

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Multiple datasets and drought indices for supporting the mitigation of and adaptation to drought in Ethiopia

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Contents

1. Background to the fellowship project

- The demand for accurate hydroclimate information has been increasing across the world

- The need is greater among many data poor climate risk-prone developing countries

- Currently, there is a unique opportunity for researchers and practitioners in data poor regions due to innovation in the state-of-the-art techniques in HC data production (AghaKouchak et al., 2015)

- There are ample gridded HC data products with a global coverage at multiple spatial temporal resolutions freely available for researchers and practitioners

- However, the accuracy and representativeness of most global datasets are quite different from place to place and between data products

- Most of the data have been tested and being widely used in many developed countries

- The application of these global scale data products in the developing countries very low and at its early stage for several reasons

Con…

- The accuracy of most data products are not tested and well known
- the quality of data are different for different applications
- Lack of awareness on their availability
- Lack of knowledge & skill to use and analyse gridded data products
- Some of them are less accurate at a given region

- Hence, there is an urgent need to produce representative quality data, or explore globally available data products, evaluate their reliability for specific application, and communicate results both for users and producers

- On the other hand, many drought monitoring has been developed following the emergence of multiple earth observation data products
    - SPI PDSI, SPEI, SRHI, SSI… need to be tested for African region

objectives

- Identify geospatial datasets and drought indices that can have better performance in Ethiopia;
- Identify the large scale atmospheric driver of drought development in Ethiopia by analyzing the coupled spatiotemporal drought variability and large scale climate oscillation systems;
- Evaluate the performance of geospatial datasets in simulating the coupled spatiotemporal drought variability and large scale climate oscillation systems, and
- Fellows and other young researcher capacity building through training and networking.

3 Methodology

underlying assumption

- Drought can be defined as a temporary reduction of water availability compared to the normal values extending along a significant period of time and over a large region.

- From disciplinary perspective drought can be classified into 4 categories: 1) Meteorological, 2 agricultural, 3) hydrological & 4) socioeconomic

- Meteorological drought is one of the primary causes to the other drought types

- The impacts of drought can be determined by its frequency, magnitude, duration, and geographical coverage

- Hydrometeorological indicators and indices are commonly used for drought monitoring and forecasting works

Data type and sources

- 20 precipitation data

No.	Dataset	Record length	Temporal resolution	Spatial resolution	Data category
Gauge interpolated data					
1	CPC	1979-present	Daily	0.5°	Gauge
2	CRU	1901-present	Monthly	0.5°	Gauge
3	GPCC	1901-present	Monthly	1°	Gauge
4	PREC/L	1948-present	Monthly	1°	Gauge
Satellite only data					
5	AIRS	2003-present	Monthly	1°	Satellite
6	CHIRP	1981-present	Monthly	0.05°	Satellite
7	PERSIANN	2001-present	Monthly	0.25°	Satellite
8	PERSIANN-CCS	2003-present	Monthly	0.04°	Satellite
Reanalysis data					
9	ERA5	1979-present	Monthly	0.28°	Reanalysis
10	FLDAS	1982-present	Monthly	0.1°	Reanalysis
11	GLADS	1979-present	Monthly	1°	Reanalysis
12	MERRA2	1980-present	Monthly	0.66°x0.50°	Reanalysis
Multisource data					
13	ARC2	1996_present	Daily/monthly	0.1°	Satellite-gauge
14	CHIRPS	1981-present	Daily	0.05°	Satellite-gauge
15	GPM	2001-present	Monthly	0.1°	Satellite-gauge
16	PERSIANN_CDR	1983-present	Monthly	0.25°	Satellite-gauge
17	TAMSAT	1983-present	Monthly	0.05°	Satellite-gauge
18	RFE2		Monthly	0.1°	Satellite-gauge
19	TerraClimate	1958-present	Monthly	0.04°	Satellite-gauge
20	TRMM 3B43	1998-present	Monthly	0.25°	Satellite-gauge
Reference data					
1	ETH-SaGa	1983-present	Monthly	0.04°	Satellite-gauge
2	In-situ stations	1983-present	monthly		Gauge (126)

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➢ 4 PET, 2 RH, 4 Soil moisture & 1 vapor pressure deficit

No.	Dataset	Record length	Temporal resolution	Spatial resolution	Variable type	Data category
PET data						
1	CRU	1901-present	Monthly	0.5°	PET & Prec.	Gauge interpolated
2	ERA-5	1979-present		~0.28°	PET & Prec.	Model simulation
3	GLDAS-Noah	2000-present	Monthly	1°	PET & Prec.	Model simulation
4	TerraClimate	1958-present	Monthly	0.04°	PET & Prec.	Multisource
Soil moisture data						
1	CPC	1979-present	Monthly	0.5°	Soil moisture	Gauge interpolated
2	ERA-5	1979-present		~0.28°	Soil moisture	Model simulation
3	FLDAS	1982-present	Monthly	0.1°	soil moisture	Model simulation
4	MERRA-2	1980-present	Monthly	0.66°x0.5°	Soil moisture	Model simulation
Relative humidity data						
1	AIRS	2002-present	Monthly	1°	Relative humidity	Satellite
2	ERA-5	1979-present		~0.28°	Relative humidity	Model simulation
VPD						
1	TerraClimate	1958-present	Monthly	0.04°	VPD	Multisource
Reference data						
1	In-situ stations	1983-2018	Monthly	point	Precipitation	In-situ
2	ETH-SAGA	1983-present	Monthly		Precipitation	Gage-satellite

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- 4 Sea surface temperature datasets for teleconnection analysis
  - Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST, Rayner et al., 2003) 1°x1°
  - NOAA’s Centennial insitu Observation-Based Estimates (NOA_ COBE, Hirahara et al., 2014) 1°x1°
  - NOAA’s Extended Reconstructed Sea Surface Temperature (NOAA_ERSST, Smith et al., 2008) 2°x2°
  - NOAA’s Optimum Interpolation Sea Surface Temperature (NOAA_OISST, Reynolds et al., 2002) 1°x1°

Cont..

- Criteria to select these datasets:
  - Spatial resolution (<1°)
  - Experience in the other part of the world
  - Quality (not has missing data)
  - Data format and ease of accessibility

- Methods used to detect drought condition
  - Standardized Precipitation Index (SPI; McKee et al., 1993)
  - Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2012)
  - Standardized Soil moisture Index (SSI; Hao and AghaKouchak, 2013)
  - Standardized Relative Humidity Index (SRHI; Farahmand et al., 2014)
  - Standardized Vapor Pressure Deficit (SVPD; Behrangi et al., 2015)

Cont..

- Criteria to select these drought indices:
  - Wider application both in research and operational activities
  - Comparability
  - Some of the indices (SPI and SPEI) recommended by WMO
  - Some of the indices (SHI & SVDI) acknowledged for their skill of early drought detection

- Drought indices were generated at 3- and 12month and for the spatially different 3 wet seasons (MAM, JJAS and SON)

- Results provide positive and negative values at monthly time scales, & -1 is a threshold to define drought months

Evaluation methods

- Visual comparison between the reference and studied data products for selected major drought episodes (1984, 2002, 2009, 2015) and for drought frequency
- Correlation between drought indices of the reference and studied data products
- Critical success Index (CSI) method. It considered only SPI values <=-1 between the reference and studied data products & has four performance indicators:
  - $POD = \frac{H}{H+M}$
  - $MR = \frac{M}{H+M}$
  - $FAR = \frac{F}{H+F}$
  - $CSI = \frac{H}{H+F+M}$

Results

Drought detection performance for 20 precipitation data products

- Most datasets showed inconsistent and weak performance in capturing major drought events Figure1_Major_drought_events.docx
- Data that showed better performance compared to the other
  - CHIRPS, FLDAS, CHIRP, TAMSAT and TerraClimate better for 1984
  - CHIRPS, ERA5 ARC2, and RFE2 better in capturing the 2002 drought
  - CHIRPS, ERA5, FLDAS, AIRS, GPM, the three PERSIANN data and TRMM better in capturing the 2009 drought
  - CHIRPS, ERA5, FLDAS, CHIRP, GPM, PERSIANN/CCS, PERSIANN/CDR, TAMSAT and TRMM better in capturing the 2015 drought

Cont..

- Few data products able to capture drought frequencies:
  - CHIRPS followed by FLDAS, GPCC, ARC2, GPM, PERSIANN/CCS, PERSIANN, RFE and TRMM attempted to represent the 3-month drought
  - Only 3 data products (CHIRP, CHIRPS and PERSIANN/CDR) able to represent the 12-month drought frequency[Figure2_3&12-month_drought_frequency.docx]
  - Correlation and CSI values showed better performance for 3-month than 12-month time scale drought events
  - Spatial pattern of POD, MR, FAR,& CSI were mapped for both 3- and 12-month drought. Eg., CSI distribution for 3-month[Figure-3_CSI_SPI3.docx]

Cont..

Performance result for SPEI, SSI, SRH, SVDI

- Most data and drought indices showed inconsistent and poor performance in all measures

Example:

- Performance to capture major drought events, Figure4_SPEI_major_drought.docx, Figure5_SSI_major_dorought.docx Figure6-RHI_SVDI_major drought.docx

- Performance in representing drought frequency Frequency_SPEI_SSI_SHI.docx

- All the four CSI measures for SPEI, SSI and SRH are lower compared to the SPITable_2.docx

Cont..

- SRHI and SVDI did not show better performance in capturing drought intensity and onset earlier than SPI for wet seasons. Example:

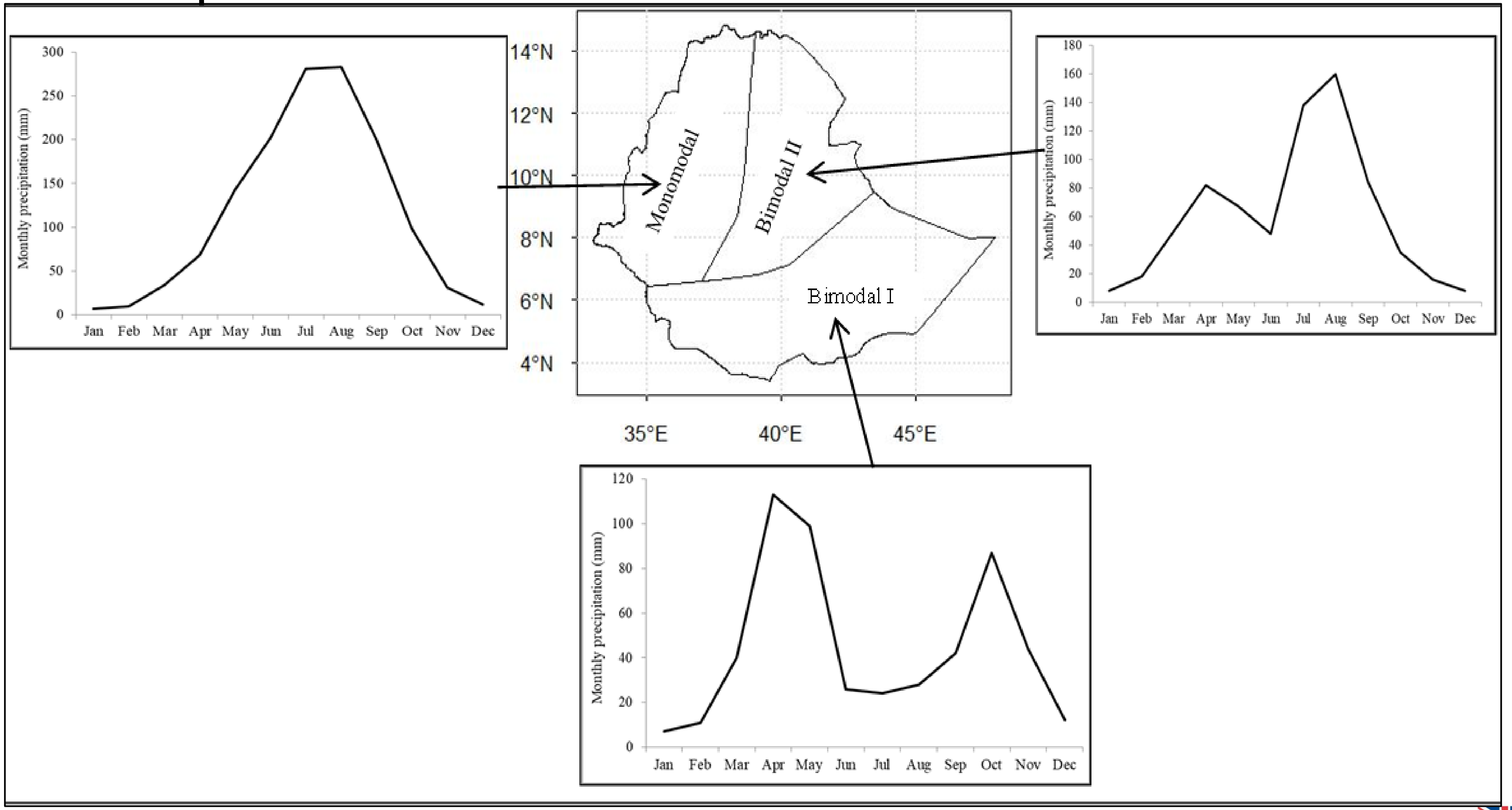
  - MAM drought in 2009 and 2011[Figure7_MAM_SPEI_2009_2011.docx](Figure7_MAM_SPEI_2009_2011.docx), Figure8_MAM_SRHI_SVDI.docx

  - JJAS drought in 2015[Figure9_SPEI_JJAS_2015.docx](Figure9_SPEI_JJAS_2015.docx), Figure10_JJAS_SHI_SVDI_2015.docx

  - SON drought in 2003 and 2016[Figure11_SPEI_OND_2003&2016.docx](Figure11_SPEI_OND_2003&2016.docx), Figure12_OND_SRHI_SVDI_2003&2016.docx

Teleconnection between SPI and global sea surface temperature for three wet seasons in Ethiopia, and the consistency of four SSTs

- Teleconnection analysis was made for 3 spatially different rainfall season over Ethiopia



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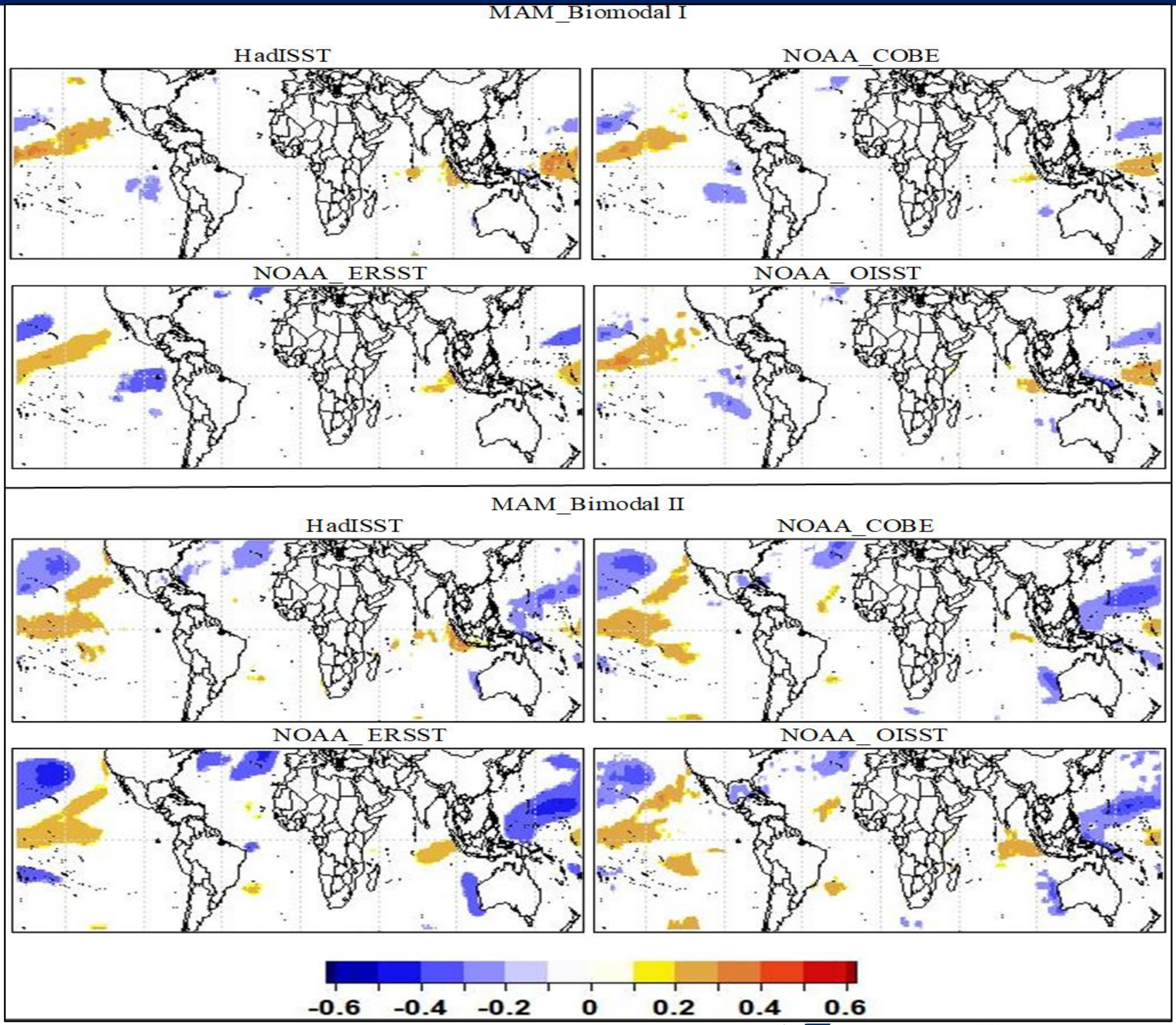
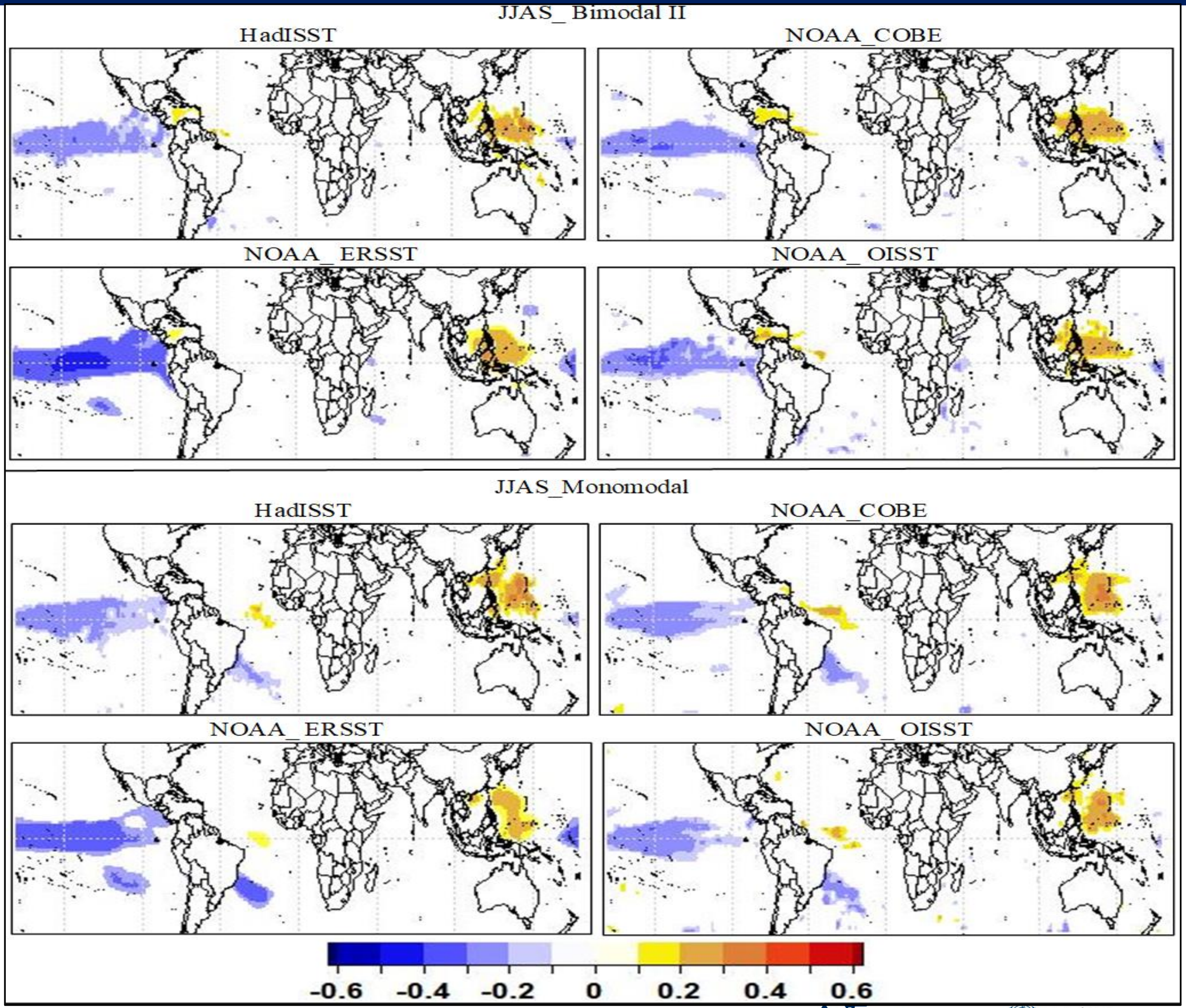
- Correlation analysis was conducted at zero, one month, two months and three months lag-times
- The result of correlation at zero lag-time is presented here as the significance of correlation gradually decreased with increased lag-time for all SST products and for all wet seasons

- The general patterns and strength of correlation between SPI and SST more or less the same for most SST data and
- JJAS season, statistically significant negative correlation with SST at central and eastern parts of Pacific Ocean, and statistical significant negative correlation with SST at the western part of Pacific Ocean.

Cont..


MAM_Biomodal I
HadISST
NOAA_COBE
NOAA_ERSST
NOAA_OISST
MAM_Bimodal II
HadISST
NOAA_COBE
NOAA_ERSST
NOAA_OISST
-0.6
-0.4
-0.2
0
0.2
0.4
0.6

Cont..


JJAS_ Bimodal II
HadISST
NOAA_COBE
NOAA_ ERSST
NOAA_ OISST
JJAS_Monomodal
HadISST
NOAA_COBE
NOAA_ ERSST
NOAA_ OISST
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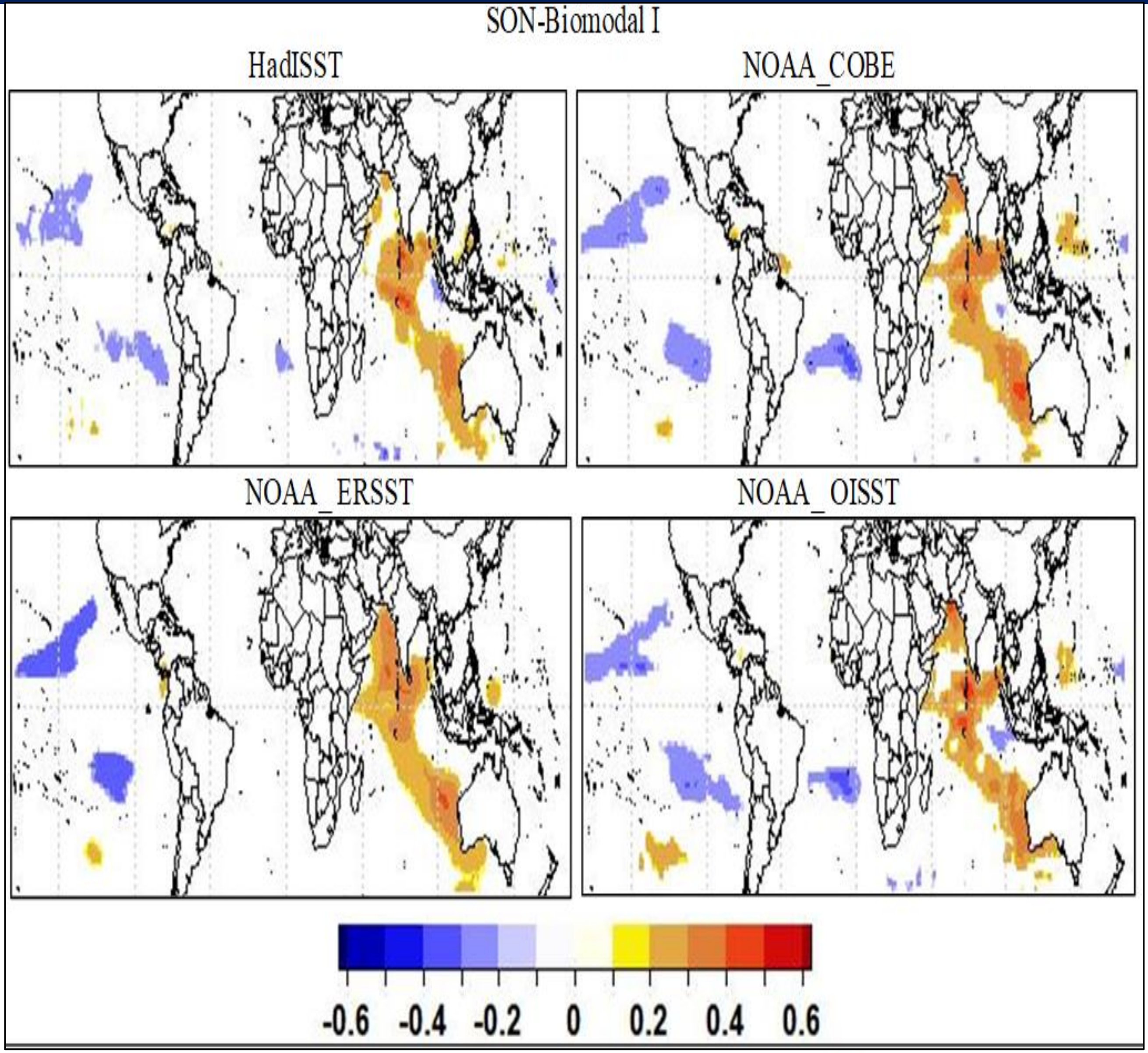
-0.4
-0.2
0
0.2
0.4
0.6

Cont..



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Some possible reasons for poor performance for most data and performance variation among data products

- Variation in spatial resolutionFigure13_correlation_CSI.docx
- Declined number of observation considered for interpolation
- Variation in methodologies and algorism in estimating weather data from satellite and in simulating model products
- Absence of in-situ data sets used for calibration and validation over Ethiopia in estimating RH from satellite observation

Activities accomplished related capacity building and networking

- Acquired new skill and experience in data mining from big global data sources, big data management & software packages (CDT, CDO and R)

- Capacity building for 15 selected researchers: training on two software packages (CDT, CDO and SWAT)

- Two workshops and one training programmes were implemented

- Networks network with, AAU, DMU, NMA, AAS, ICPAC, and University of Nairobi

Conclusion

- Three (CHIRPS followed by FLDAS & GPCC) precipitation datasets have better performance compared to the others

- Almost all global PET datasets can provide good SPEI value if used with Ethiopian gridded data

- FLADS followed by ERA5 soil moisture data are relatively better than the other soil moisture data in estimating drought phenomena

- SRHI and SVDI did not show better and consistent performance in capturing drought onset earlier than SPI

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- The result also implies the need that we African should a lot to have representative and reliable hydroclimate data

Two papers were produced and submitted to journal article for publications

Two more papers are under preparation

Thank you for your attention!